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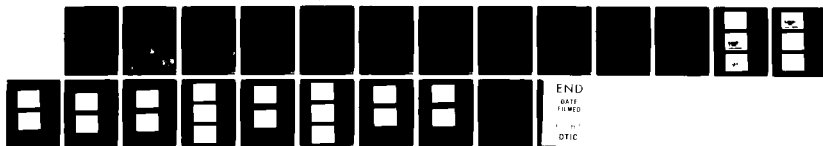
IMPROVEMENTS IN MULTISPECTRAL IMAGE SMOOTHING(U)
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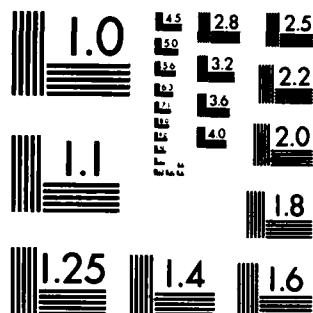
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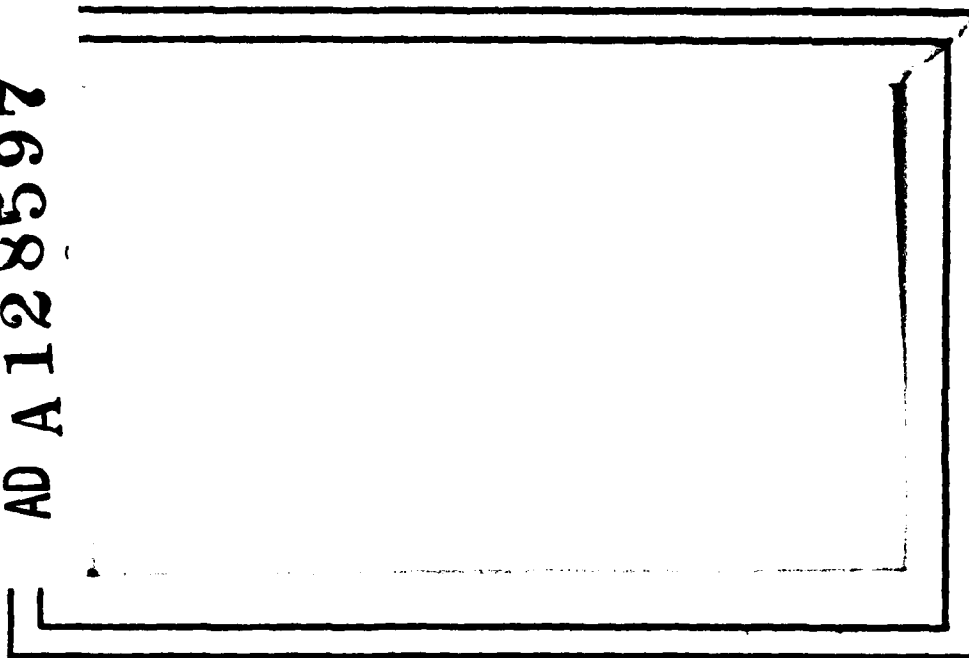




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IMPROVEMENTS IN MULTISPECTRAL
IMAGE SMOOTHING

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ABSTRACT

Two problems with the multispectral smoothing technique of Pietikainen and Rosenfeld are that random sampling fluctuations in the scatter plot may produce spurious pixel classes, and that noise pixels sufficiently distinct from their neighbors will not be smoothed at all. These problems can be overcome by the use of variable-neighborhood smoothing in the scatterplot, and by a judicious use of median filtering in conjunction with multispectral smoothing.

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1. Introduction

A new smoothing technique, which uses the global histogram of an image to guide a local averaging process, was proposed by Narayanan and Rosenfeld [3]. Recently, Pietikäinen and Rosenfeld [5] have generalized this technique to handle multispectral images. The substance of these techniques is that a pixel is averaged with only a subset of its neighbors, specifically those that satisfy both the following conditions: Firstly, the gray level of the neighbor should occur more frequently than that of the given pixel. Secondly, there should be in the histogram of the image no significant concavity between the gray level of the neighbor and that of the given pixel. (For a multispectral image, the scatterplot of one band against another is used instead of the histogram.) The effect of this is that a pixel is averaged only with more typical (more common) neighbors of the same population.

In practice, the histogram (or scatterplot) of an image will have many fluctuations that are merely artefacts of limited sampling. These fluctuations produce spurious peaks which mislead the smoothing process. The authors mentioned above coped with this problem by uniformly smoothing the histogram (or scatterplot) itself. However, it has been remarked [4,6] that in a histogram the more common values have their frequencies estimated fairly reliably, while it is the rarer values that are more

subject to sampling errors. This has lead us to investigate the effects of nonuniform histogram smoothing.

Another difficulty with the techniques mentioned above is that a noise pixel, if sufficiently distinct, may well be judged to belong to a separate population from its neighbors, and not be smoothed at all. So we have also considered some methods for removing such isolated noise spots.

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2. Algorithm and experiments

For these experiments, we used the same smoothing technique as Pietikäinen and Rosenfeld, except for the way the scatterplot is smoothed. They averaged the frequency of a point in the scatterplot with the frequencies in a 3-by-3 neighborhood in the scatterplot. We instead construct progressively larger neighborhoods around the point until the total frequency within one of the neighborhoods reaches or exceeds a threshold value S . Thus little smoothing is done in those regions of the scatterplot where frequencies are high, and more smoothing is done where they are low. We start with a trivial 1 by 1 neighborhood (the point alone), and increase the side of the neighborhood in steps of two: 3 by 3, 5 by 5, and so on. We call this "optional" scatterplot smoothing since a point in the scatterplot with sufficient frequency will not be smoothed at all. We also used a variant called "obligatory" scatterplot smoothing, in which we start the series of neighborhoods with the 3-by-3 size, so that some smoothing is always performed at every point in the scatterplot. (Notice that the neighborhood size used for smoothing the histogram is quite unrelated to the neighborhood size used for smoothing in the image, which in this report is always 3 by 3.)

Figure 1 shows the red and green bands of a color picture of a house (gray levels 0 to 63 in each band), together with the 64 by 64 scatterplot of red against green, in which the

frequencies are displayed as brightnesses, after both linear and logarithmic scaling. Figures 2 and 3 show the results of 5 and 10 iterations of Pietikäinen's method without any smoothing of the scatterplot. Figures 4 and 5 show the results of 5 and 10 iterations using optional scatterplot smoothing with threshold value $S=300$. Notice that the images are more smoothed than those in Figures 2 and 3, and that the scatterplots are more cleanly separated into fewer peaks. For comparison, Figure 6 shows the result of 10 iterations with a different threshold value, $S=500$. The difference between Figures 5 and 6 seems minor, although the higher value of S causes more smoothing of the scatterplot and image. Figures 7 and 8 are the same as 4 and 5, respectively, except that obligatory scatterplot smoothing is used. The difference in the results is very slight. Obligatory smoothing leaves the scatterplot more diffuse. The images themselves are a little smoother, although this is not apparent in the figures here, because of the limited gray-level resolution.

Pietikäinen's method has a parameter λ , which is a threshold on the significance of concavities in the scatterplot. The lower the value of λ , the deeper a concavity needs to be before it is considered significant. Figures 7 and 8 were created with $\lambda=0.1$. Figures 9 and 10 are analogous, with $\lambda=1.0$. Figures 11 and 12 are the same, except that $\lambda=0.01$. It can be seen that the high value of λ reduces the smoothing, because the scatterplot

is divided into too many peaks. With the low values, only the significant peaks are respected. So the smoothing effect is greater, and does not depend so much on the precise value of λ .

Thus we can exert some control over the degree of smoothing by adjusting the parameters S and λ , and by the selection of optional or obligatory smoothing. However, the results are not unduly sensitive to these choices, so their exact settings are not critical. We have chosen to use $\lambda=0.1$, $S=300$, and obligatory smoothing for all the images in this report, unless otherwise stated.

In order to study the effectiveness of these smoothing techniques on very noisy images, we added noise to our house image. Figure 13 shows the house image with independent, zero-mean Gaussian noise of standard deviation $\sigma=5$ added to both bands. Figures 14 and 15 show the results of 5 and 10 iterations of our smoothing technique. The noise has mostly been removed, except for some remaining specks, and the scatterplot has almost condensed into three main peaks. We applied 3 by 3 median filtering to each band of Figures 14 and 15; the results appear in Figures 16 and 17, respectively. The remaining noise spots have been almost entirely removed, and the scatterplot is further condensed, although some of the fine details of the original image have been obliterated. We also tried median filtering before smoothing. Figure 18 shows the results of 3 by 3 median

filtering on both bands of the noisy image (Figure 13).

Figures 19 and 20 show the results of 5 and 10 iterations of smoothing on this median-filtered image. The results are similar to those obtained by applying median filtering after smoothing, but not quite so good. Another standard technique for removing noise is mean filtering. We therefore tried 5 by 5 mean filtering on our noisy picture (Figure 21), and then applied 10 iterations of smoothing (Figure 22). It is interesting that the smoothing process is able to reconstruct sharp edges -- pixels on a blurred edge are forced to move into one region population or the other. However, many noise spots still remain, since mean filtering cannot remove all traces of noise spots.

In Figures 23 and 24 we see the effects of 5 and 10 iterations respectively of a combined process of smoothing followed by 3-by-3 median filtering on every iteration. A lot of detail has been lost, and the result is a simplified, cartoon-like version of the original.

As suggested by Pietikäinen and Rosenfeld [5], we applied this smoothing technique to LANDSAT images, to see whether smoothing would result in any improvement in classification, as measured by comparison with the ground truth [2]. Unfortunately, no consistent improvement was found. It seems that in LANDSAT images at least, the large number of classes present in each image causes confusion of populations in the scatterplot, leading to misclassification.

3. Concluding remarks

The use of the global distribution of pixel values in an image in order to guide a smoothing process is a powerful and effective technique for smoothing images without blurring edges. In this report we have investigated ways of overcoming two problems with this technique: spurious peaks in the image's histogram (or scatterplot) caused by random sampling variation, and isolated noise spots which appear to belong to a different population from their neighbors and are hence not smoothed. The first problem can be overcome by non-uniform smoothing of the scatterplot (or histogram), and the second by a judicious use of median filtering. Both of these processes are important adjuncts to the original smoothing technique, especially for noisy images.

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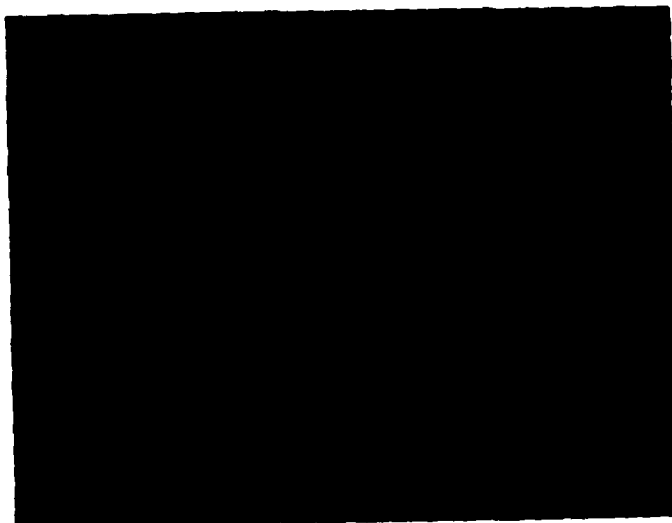


Figure 1. Original red (left) and green (right) bands of house picture, with plain (left) and logarithmic (right) scatterplots. Following figures show only logarithmic scatterplots.



Figure 2. A x 5 iteration of Pietikäinen's smoothing (without any scatterplot smoothing, $\lambda = 0.5$).



Figure 3. Same as Figure 2 but after 10 iterations.

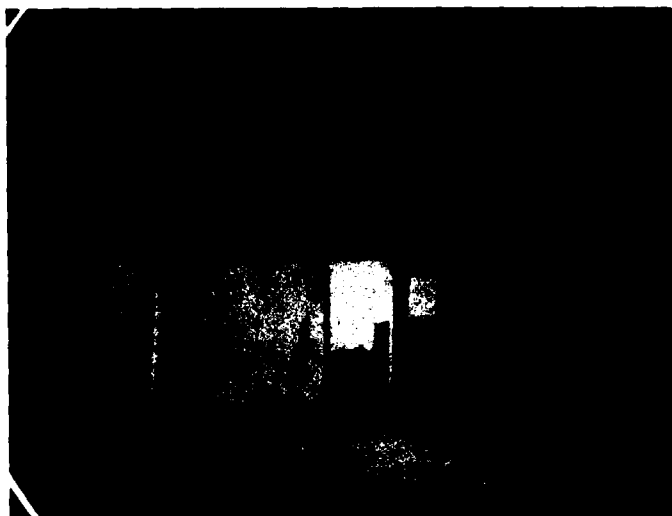


Figure 4. After 5 iterations
with optional scatterplot
smoothing, $S=300$, $\lambda=0.1$.



Figure 5. Same as Figure 4,
but after 10 iterations.

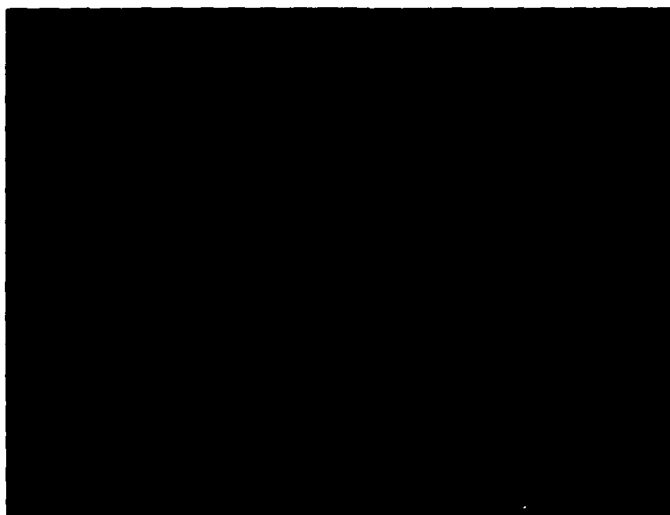


Figure 6. After 10 iterations
with optional scatterplot
smoothing, $S=500$, $\lambda=0.1$.



Figure 7. After 5 iterations with obligatory scatterplot smoothing, $S=300$, $\lambda=0.1$.

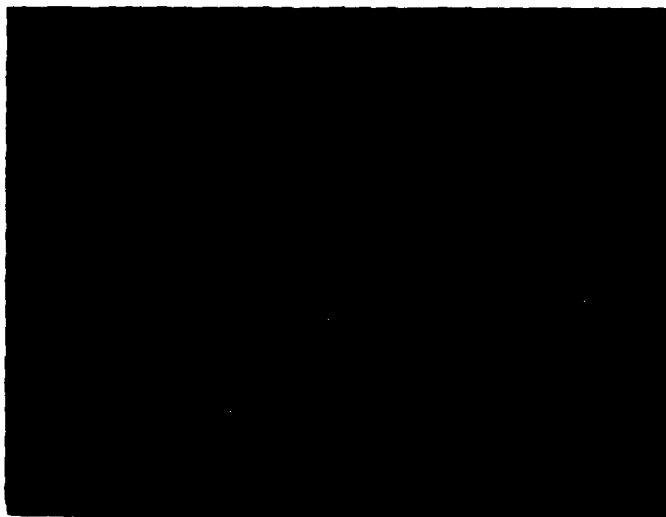


Figure 8. Same as Figure 7, but after 10 iterations.

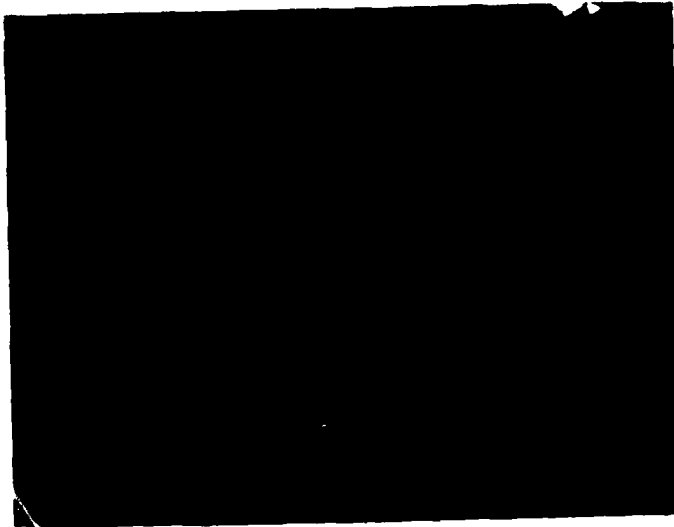


Figure 9. After 5 iterations with obligatory scatterplot smoothing, $S=300$, $\lambda=1.0$.

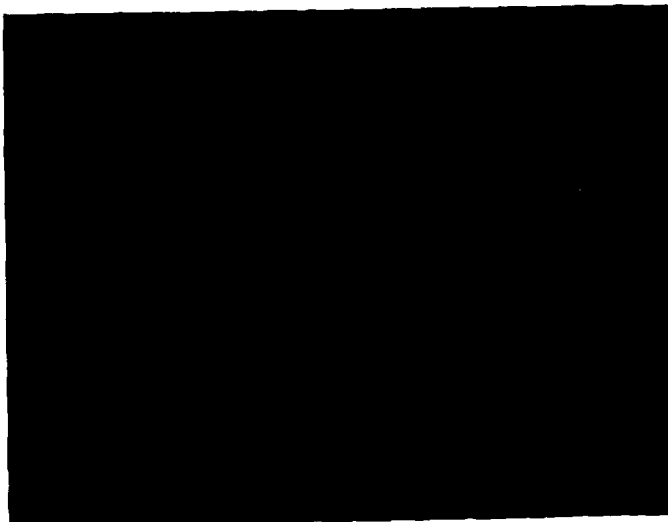


Figure 10. Same as Figure 9, but after 10 iterations.



Figure 11. After 5 iterations with obligatory scatterplot smoothing, $S=300$, $\lambda=0.01$.



Figure 12. Same as Figure 11, but after 10 iterations.



Figure 13. Noisy house picture, $\sigma=5$.

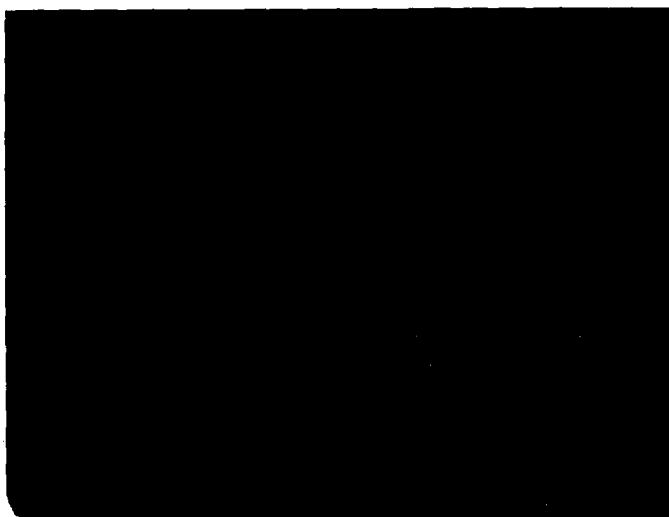


Figure 14. After 5 iterations smoothing on Figure 13.



Figure 15. After 10 iterations of smoothing on Figure 13.



Figure 16. After 3
by 3 median filtering
on Figure 14.



Figure 17. After 3
by 3 median filtering
on Figure 15.



Figure 18. After 3 by
3 median filtering on
Figure 13.



Figure 19. After 5 itera-
tions of smoothong on
Figure 18.



Figure 20. After 10
iterations of smoothing
on Figure 18.



Figure 21. After 5
by 5 mean filtering
on Figure 13.

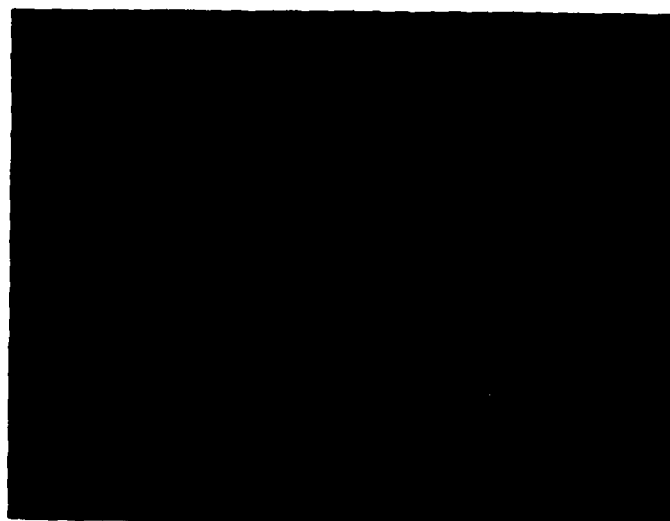


Figure 22. After 10
iterations of smooth-
ing on Figure 21.

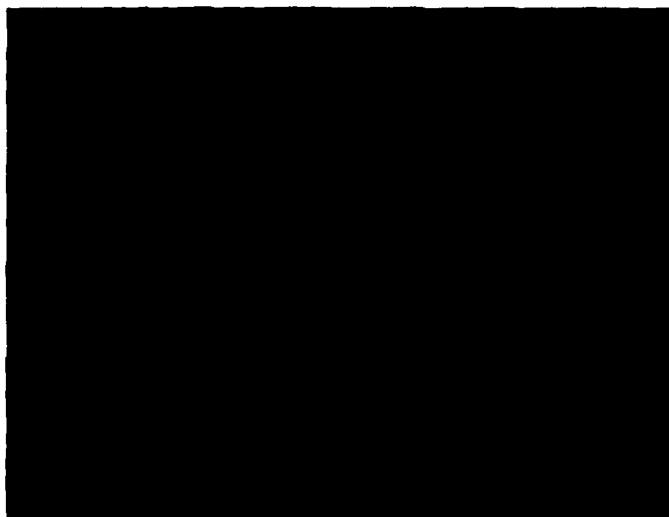


Figure 23. After 5 iterations of combined smoothing and 3 by 3 median filtering on Figure 13.



Figure 24. Same as Figure 23, but after 10 iterations.

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